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From AI Assisted to Self-Regulated Learning: Roles of Digital Literacy, Critical Thinking, and Self-Efficacy among University Students

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Abstract

Artificial intelligence (AI) is rapidly transforming higher education by providing personalized and adaptive learning experiences. However, limited research has systematically examined the mechanisms through which AI-assisted learning enhances students' self-regulated learning, particularly in developing countries. Grounded in Social Cognitive Theory, Self-Regulated Learning Theory, and the Technology Acceptance Model, this study investigates the influence of AI-Assisted Learning on Self-Regulated Learning, examining the mediating roles of AI Literacy and Critical Thinking and the moderating role of AI Self-Efficacy. A quantitative cross-sectional design was employed, and survey data were collected from 225 university students enrolled in public and private universities in Somalia. The proposed model was tested using Hayes' (2022) PROCESS Macro through regression, mediation, and moderation analyses with 5,000 bootstrap resamples. The findings indicate that AI-Assisted Learning significantly improves Self-Regulated Learning, AI Literacy, and Critical Thinking. Moreover, AI Literacy and Critical Thinking significantly enhance Self-Regulated Learning and partially mediate the relationship between AI-Assisted Learning and Self-Regulated Learning, with Critical Thinking demonstrating the stronger indirect effect. The results further reveal that AI Self-Efficacy positively moderates the relationship between AI-Assisted Learning and AI Literacy, indicating that students with greater confidence in using AI technologies gain stronger learning benefits. By integrating technological, cognitive, and psychological factors into a unified framework, this study addresses an important gap in the AI-in-education literature and provides empirical evidence from an underexplored context. The findings demonstrate that AI-assisted learning promotes autonomous learning by fostering AI literacy, critical thinking, and self-efficacy, offering valuable theoretical and practical implications for the effective integration of AI in higher education.

1. Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technologies in higher education, fundamentally changing how students access information, acquire knowledge, and engage in learning. Recent advances in generative AI, intelligent tutoring systems, adaptive learning platforms, and conversational agents have enabled learners to receive personalized feedback, instant academic support, and adaptive learning experiences that were previously unattainable (Dwivedi et al., 2023; Holmes et al., 2019). Consequently, universities worldwide are increasingly integrating AI-powered technologies into teaching and learning to improve educational quality, learner engagement, and academic performance. As AI becomes an integral component of digital education, understanding how AI-assisted learning influences students' learning behaviors has become a critical concern for researchers, educators, and policymakers.

The relationship between AI-assisted learning and self-regulated learning, however, is unlikely to be direct. Students who engage frequently with AI technologies are expected to develop AI literacy the ability to understand AI capabilities, verify AI-generated information, and use AI responsibly (Long & Magerko, 2020; D. T. K. Ng et al., 2021) and to strengthen their critical thinking as they evaluate the accuracy and credibility of AI-generated responses(Kasneci et al., 2023). Because effective self-

regulated learners must not only use digital tools but also critically evaluate the information those tools produce, AI literacy and critical thinking are proposed here as parallel mechanisms linking AI-assisted learning to self-regulated learning. Students' confidence in using AI technologies, or AI self-efficacy, may further determine how much benefit they extract from AI-assisted learning: Social Cognitive Theory(Bandura, 1986) suggests that individuals with higher self-efficacy are more willing to adopt new technologies and persist through difficulty, so AI self-efficacy is proposed to strengthen the effect of AI-assisted learning on AI literacy.

Despite growing scholarly interest, three gaps remain. Most studies have examined the direct effects of AI-assisted learning on performance, engagement, or technology acceptance, with little attention to the mechanisms through which it might enhance self-regulated learning (Dwivedi et al., 2023; Zawacki-Richter et al., 2019). Existing research has also relied on Social Cognitive Theory, Self-Regulated Learning Theory, or the Technology Acceptance Model in isolation rather than integrating them to explain how technological, cognitive, and psychological factors jointly shape learning behavior. Finally, most evidence comes from developed-country contexts, leaving AI-assisted learning in developing countries including Somalia, where AI adoption is expanding rapidly but remains empirically underexplored largely untested.

This study addresses these gaps by testing an integrated model, grounded in Social Cognitive Theory (Bandura, 1986), Self-Regulated Learning Theory (Zimmerman, 2000), and the Technology Acceptance Model (Davis, 1989), in which AI-Assisted Learning predicts Self-Regulated Learning both directly and indirectly through AI Literacy and Critical Thinking, with AI Self-Efficacy moderating the link between AI-Assisted Learning and AI Literacy. Specifically, the study addresses the following research questions:

RQ1: How does AI-Assisted Learning influence Self-Regulated Learning, AI Literacy, and Critical Thinking among university students?

RQ2: Do AI Literacy and Critical Thinking mediate the relationship between AI-Assisted Learning and Self-Regulated Learning?

RQ3: Does AI Self-Efficacy moderate the relationship between AI-Assisted Learning and AI Literacy among university students?

By answering these questions, this study contributes an integrated theoretical framework, empirical evidence on two simultaneous mediating mechanisms and one moderating mechanism that remain underexplored in the AI-in-education literature, and new evidence from an underrepresented higher-education context, with practical implications for universities seeking to design effective AI-enabled learning environments.

The remainder of the paper proceeds as follows: Section 2 reviews the literature and develops the hypotheses; Section 3 describes the methodology; Section 4 reports the results; Section 5 discusses the findings; and Section 6 concludes with the study's limitations and directions for future research.

2. Literature Review and Theoretical Framework

2.1 Overview of Prior Research

The rapid advancement of artificial intelligence (AI) has transformed higher education by introducing intelligent technologies that enhance teaching, learning, assessment, and academic support. AI-powered educational applications, including intelligent tutoring systems, adaptive learning platforms, generative AI tools such as ChatGPT, automated feedback systems, and learning analytics, are increasingly integrated into university learning environments to personalize instruction, improve student engagement, and facilitate knowledge acquisition (Crompton & Burke, 2023; Kasneci et al., 2023; Zawacki-Richter et al., 2019). These technologies have shifted learning from traditional teacher-centered approaches toward learner-centered environments in which students actively regulate their own learning processes through continuous interaction with AI-driven systems.

Recent studies have demonstrated that AI-assisted learning can improve students' academic performance, motivation, learning efficiency, and problem-solving abilities by providing immediate feedback, personalized recommendations, and adaptive instructional support(Chen & Aklikokou, 2020; Ouyang et al., 2023). The emergence of generative AI has further expanded these opportunities by enabling students to receive instant explanations, generate learning materials, summarize academic content, and engage in interactive conversations that support deeper understanding of complex concepts (Kasneci et al., 2023). Consequently, universities worldwide recognize AI as a strategic educational technology capable of promoting personalized learning and improving educational quality.

Despite these advancements, the educational value of AI extends beyond technology adoption itself. Increasing evidence suggests that the effectiveness of AI-assisted learning largely depends on learners' cognitive, behavioral, and psychological capabilities rather than merely their access to AI technologies (Bond et al., 2024; Ifenthaler & Schumacher, 2023). Students must possess sufficient digital competencies to evaluate AI-generated information, critically interpret algorithmic recommendations, and effectively integrate AI into their learning activities. Without these competencies, excessive reliance on AI may reduce independent learning, weaken critical thinking, and negatively influence academic integrity (Kasneci et al., 2023).

Among the learner characteristics receiving increasing scholarly attention are digital literacy, critical thinking, AI self-efficacy, and self-regulated learning. Digital literacy enables students to navigate digital environments, critically evaluate online information, and responsibly use AI technologies for academic purposes (Ng, 2012; van Laar et al., 2017). Critical thinking enables learners to question AI-generated outputs, recognize misinformation, and make evidence-based academic judgments rather than accepting AI responses uncritically (Facione, 1990). AI self-efficacy reflects students' confidence in their ability to effectively utilize AI technologies, influencing both technology acceptance and learning performance(Bandura, 1986; Compeau & Higgins, 1995). Self-regulated learning represents students'

ability to independently plan, monitor, evaluate, and adapt their learning behaviors to achieve academic goals (Zimmerman, 2000).

Although these constructs have individually received substantial empirical attention, previous research has generally investigated them in isolation. Many studies have focused primarily on the educational effectiveness of AI tools, while others have examined digital literacy, critical thinking, or self-regulated learning as independent educational outcomes. Comparatively fewer studies have integrated these variables within a comprehensive framework that explains the mechanisms through which AI-assisted learning enhances students' self-regulated learning. Moreover, the mediating roles of digital literacy and critical thinking, together with the moderating influence of AI self-efficacy, remain insufficiently explored, particularly in developing countries where digital transformation in higher education is still evolving.

This limitation is particularly evident in Sub-Saharan Africa and Somalia, where AI adoption in higher education is increasing despite significant disparities in digital infrastructure, technological readiness, and AI-related competencies(Ahmad Malik et al., 2025; Maluleke, 2025). Existing studies from developed countries may therefore not fully explain students' learning behaviors in resource-constrained educational contexts. Consequently, there remains limited empirical evidence regarding how AI-assisted learning contributes to self-regulated learning through cognitive and digital capability development among university students in developing countries.

To address these gaps, the present study develops an integrated research model that examines the direct relationship between AI-assisted learning and self-regulated learning while simultaneously investigating the mediating roles of digital literacy and critical thinking and the moderating role of AI self-efficacy. By integrating these constructs into a unified framework, this study contributes to the growing literature on AI-supported learning and provides empirical evidence regarding the psychological and cognitive mechanisms through which AI technologies enhance independent learning among university students.

2.2 AI-Assisted Learning and Self-Regulated Learning

AI-assisted learning refers to the use of AI-powered technologies including intelligent tutoring systems, adaptive learning platforms, conversational AI, recommender systems, learning analytics, and generative AI applications to facilitate students' learning processes and improve academic outcomes (Luckin & Holmes, 2016; Zawacki-Richter et al., 2019). Unlike conventional digital learning technologies, AI systems continuously analyze learners' behaviors and provide personalized recommendations, adaptive feedback, and individualized instructional support that align with students' learning needs.

One of the most significant educational outcomes associated with AI-assisted learning is the development of self-regulated learning (SRL). According to Zimmerman (2000), self-regulated learning refers to learners' proactive ability to plan, monitor, regulate, and evaluate their own learning activities in pursuit of academic goals. Self-regulated learners actively manage their cognitive, motivational, and behavioral processes by setting learning objectives, selecting appropriate strategies, monitoring

progress, and reflecting on learning outcomes. These competencies are increasingly recognized as essential for successful learning in digitally mediated educational environments.

Recent educational technology research suggests that AI-assisted learning provides several mechanisms that facilitate self-regulated learning. First, AI systems deliver immediate formative feedback that enables learners to continuously monitor their academic progress and identify knowledge gaps before they become learning obstacles(Chen et al., 2020). Second, adaptive learning technologies personalize instructional content according to learners' prior knowledge, learning pace, and performance, allowing students to regulate their learning more efficiently (Ifenthaler & Schumacher, 2023). Third, AI-powered recommendation systems assist learners in selecting appropriate learning resources, improving strategic learning behaviors and supporting autonomous knowledge construction (Ouyang et al., 2023).

The rapid emergence of generative AI has further strengthened these capabilities. Applications such as ChatGPT enable students to obtain immediate explanations, summarize complex concepts, generate practice questions, receive writing assistance, and engage in interactive academic discussions. These features encourage students to independently solve academic problems, evaluate multiple learning strategies, and reflect upon their understanding, thereby reinforcing essential dimensions of self-regulated learning (Kasneci et al., 2023). Recent evidence further suggests that generative AI can promote learner autonomy, personalized learning, and metacognitive engagement when students critically evaluate AI-generated content rather than relying on it passively (Bond et al., 2024).

From a theoretical perspective, Social Cognitive Theory (Bandura, 1986) explains that learning is influenced by reciprocal interactions among personal factors, behaviors, and environmental conditions. AI-assisted learning creates supportive digital environments that strengthen students' self-regulatory capabilities by increasing opportunities for self-monitoring, self-reflection, and mastery experiences. Similarly, Self-Regulated Learning Theory proposes that learning environments providing continuous feedback, adaptive instruction, and learner autonomy facilitate students' regulation of cognitive, motivational, and behavioral processes (Zimmerman, 2000).

Empirical evidence consistently supports the positive association between AI-assisted learning and self-regulated learning. Research has demonstrated that students who effectively utilize AI-powered learning tools exhibit higher levels of learning autonomy, goal setting, metacognitive monitoring, strategic learning, and academic persistence (Crompton & Burke, 2023; Ouyang et al., 2022). Studies have also reported that AI-supported adaptive learning environments improve students' motivation, self-management, and independent learning behaviors, which subsequently enhance academic achievement (Ifenthaler & Schumacher, 2023). Furthermore, investigations into generative AI use among university students reveal that AI can strengthen self-directed learning by providing personalized learning assistance, facilitating information retrieval, and encouraging continuous reflection on learning performance (Kasneci et al., 2023).

Nevertheless, scholars caution that the educational benefits of AI-assisted learning depend heavily on students' ability to use AI responsibly and critically. Overreliance on AI-generated responses may reduce cognitive engagement, discourage independent thinking, and weaken students' capacity to regulate their own learning (Kasneci et al., 2023). Therefore, AI-assisted learning should function as a cognitive support tool rather than a replacement for students' own learning efforts. Students who actively evaluate AI-generated information and strategically integrate AI into their learning processes are more likely to develop stronger self-regulated learning competencies than those who depend passively on AI outputs.

Although previous studies generally support a positive relationship between AI-assisted learning and self-regulated learning, most have focused on developed educational contexts. Limited empirical evidence exists regarding this relationship among university students in developing countries, particularly within African higher education institutions where AI adoption remains relatively recent and digital readiness varies substantially. Furthermore, existing studies have rarely examined the psychological mechanisms through which AI-assisted learning contributes to self-regulated learning by simultaneously considering digital literacy, critical thinking, and AI self-efficacy. Addressing these gaps provides the foundation for the present study, which proposes the following hypothesis:

H1: AI-Assisted Learning has a significant positive effect on Self-Regulated Learning.

2.3 AI-Assisted Learning and AI Literacy

Artificial intelligence (AI) has become an integral component of higher education, fundamentally changing how students’ access, evaluate, and utilize information. As AI-powered technologies become increasingly embedded in teaching and learning, the ability to use these technologies effectively has emerged as a critical competency for university students. AI literacy extends beyond basic digital competence by encompassing the knowledge, skills, and ethical awareness required to understand, evaluate, and responsibly interact with AI systems(Long & Magerko, 2020). Students with high levels of AI literacy are better equipped to recognize the capabilities and limitations of AI, critically assess AI-generated outputs, and employ AI tools to support meaningful learning rather than simply automating academic tasks.

AI-assisted learning provides a practical environment through which students develop AI literacy. Frequent interaction with AI applications such as intelligent tutoring systems, adaptive learning platforms, conversational agents, and generative AI tools exposes learners to AI functionalities, enabling them to understand how AI systems generate recommendations, personalize learning experiences, and support problem-solving activities (Kasneci et al., 2023; Zawacki-Richter et al., 2019). Through repeated engagement with these technologies, students acquire the knowledge and practical skills necessary to use AI responsibly and effectively within academic settings.

Recent studies indicate that AI-assisted learning enhances students' technological competence by improving their ability to search for information, verify AI-generated responses, interpret algorithmic recommendations, and integrate AI into learning activities (Bond et al., 2024; Crompton & Burke, 2023).

Rather than merely increasing technology usage, AI-supported learning encourages learners to become informed users who understand both the benefits and potential risks associated with AI applications. This learning process contributes to the development of AI literacy, enabling students to make informed decisions regarding when and how AI should be employed to support learning objectives.

From a theoretical perspective, the Technology Acceptance Model (TAM) suggests that continuous interaction with useful and user-friendly technologies positively influences users' knowledge, competence, and acceptance of technological innovations (Davis, 1989). Similarly, Social Cognitive Theory posits that repeated mastery experiences enhance individuals' knowledge acquisition and confidence in performing technology-related tasks (Bandura, 1986). AI-assisted learning provides these mastery experiences by allowing students to interact regularly with AI systems, thereby strengthening their technological understanding and digital competencies.

Empirical evidence increasingly supports the positive relationship between AI-assisted learning and AI literacy. Studies have shown that students who frequently utilize AI-powered educational technologies demonstrate higher levels of AI awareness, technological understanding, information evaluation skills, and responsible AI use than students with limited exposure to AI applications (Chan & Hu, 2023; Crompton & Burke, 2023). Furthermore, educational interventions incorporating generative AI have been found to significantly improve students' ability to recognize AI-generated content, evaluate algorithmic outputs, and apply AI ethically in academic contexts (Kasneci et al., 2023).

Nevertheless, scholars emphasize that exposure to AI technologies alone does not automatically result in AI literacy. Students must actively engage with AI tools, critically evaluate AI-generated information, and develop an understanding of AI limitations and ethical implications. Without such critical engagement, learners may become passive users who rely excessively on AI-generated responses without verifying their accuracy or credibility (Long & Magerko, 2020; Kasneci et al., 2023). Therefore, AI-assisted learning should be viewed as an educational mechanism that facilitates AI literacy through active interaction, reflection, and responsible technology use.

Despite growing research on AI in education, limited empirical evidence has examined the direct influence of AI-assisted learning on AI literacy among university students, particularly within developing countries where AI integration in higher education remains relatively recent. Existing studies have largely focused on technology adoption or digital literacy rather than AI-specific competencies. Addressing this gap, the present study proposes that AI-assisted learning positively contributes to students' AI literacy.

H2: AI-Assisted Learning has a significant positive effect on AI Literacy.

2.4 AI-Assisted Learning and Critical Thinking

Critical thinking is widely recognized as one of the most essential competencies required for successful learning in the digital age. It involves the ability to analyze information objectively, evaluate evidence, identify assumptions and biases, and make reasoned judgments based on logical analysis (Facione, 1990). Furthermore, AI-generated content becomes increasingly prevalent in higher education, students

must develop strong critical thinking skills to distinguish accurate information from misinformation, evaluate AI-generated responses, and make independent academic decisions(Melisa et al., 2025).

AI-assisted learning can contribute significantly to the development of critical thinking by exposing students to diverse information sources, interactive problem-solving environments, and immediate feedback mechanisms. AI-powered educational technologies encourage learners to compare multiple perspectives, verify AI-generated outputs, and engage in reflective learning processes rather than relying solely on memorization (Ouyang et al., 2022). Intelligent tutoring systems and generative AI applications also promote inquiry-based learning by encouraging students to ask questions, explore alternative explanations, and refine their understanding through iterative dialogue.

Generative AI technologies, including conversational AI systems, have introduced new opportunities for enhancing higher-order cognitive skills. Students can interact with AI to generate alternative solutions, debate different viewpoints, identify inconsistencies, and receive immediate explanations that stimulate analytical thinking. However, these benefits are realized only when learners critically evaluate AI-generated content instead of accepting responses uncritically (Kasneci et al., 2023). Consequently, AI functions not as a replacement for critical thinking but as a cognitive partner that supports reflective learning and intellectual inquiry.

Social Cognitive Theory provides a useful explanation for this relationship by suggesting that learning occurs through active interaction between individuals and their learning environments (Bandura, 1986). AI-assisted learning creates opportunities for students to engage in cognitive reflection, receive continuous feedback, and refine their reasoning abilities through repeated practice. Likewise, constructivist learning theory argues that learners develop higher-order thinking through active engagement, exploration, and knowledge construction rather than passive information reception.

Recent empirical studies consistently report positive relationships between AI-assisted learning and critical thinking. Students who actively use AI-supported learning environments demonstrate greater analytical reasoning, information evaluation, reflective judgment, and evidence-based decision-making than those relying exclusively on traditional instructional methods (Bond et al., 2024; Crompton & Burke, 2023). Furthermore, AI-supported collaborative learning environments have been shown to encourage students to challenge assumptions, identify inconsistencies, and justify academic arguments using credible evidence (Ouyang et al., 2022).

Despite these advantages, researchers caution that excessive dependence on AI may reduce opportunities for independent reasoning if students simply copy AI-generated responses without critical evaluation (Kasneci et al., 2023). Consequently, educational institutions increasingly emphasize the importance of integrating AI literacy with critical thinking instruction to ensure that students become active evaluators rather than passive consumers of AI-generated knowledge.

Although previous studies acknowledge the educational benefits of AI technologies, relatively few have empirically examined the direct influence of AI-assisted learning on students' critical thinking within

higher education, particularly in developing countries. Moreover, limited research has integrated critical thinking into comprehensive models explaining how AI-assisted learning contributes to broader educational outcomes. Therefore, the present study proposes the following hypothesis:

H3: AI-Assisted Learning has a significant positive effect on Critical Thinking.

2.5 AI Literacy and Self-Regulated Learning

AI literacy has emerged as an essential competency that enables students to effectively utilize artificial intelligence technologies to support independent learning. Beyond technical proficiency, AI literacy encompasses students' understanding of AI concepts, their ability to critically evaluate AI-generated information, awareness of ethical implications, and competence in integrating AI technologies into academic activities (Long & Magerko, 2020). As AI becomes increasingly embedded in higher education, AI literacy is expected to play an important role in strengthening students' self-regulated learning.

Self-regulated learning refers to learners' ability to proactively manage their own learning through goal setting, strategic planning, self-monitoring, and self-evaluation (Zimmerman, 2000). Students possessing strong AI literacy are better able to use AI technologies strategically to support these regulatory processes. Rather than depending passively on AI-generated responses, AI-literate students critically assess information quality, select appropriate learning resources, monitor their understanding, and adjust their learning strategies according to academic needs.

The relationship between AI literacy and self-regulated learning can be explained through Social Cognitive Theory, which emphasizes that knowledge and competence enhance individuals' self-regulatory behaviors and learning performance (Bandura, 1986). Students who understand how AI systems function are more confident in selecting appropriate AI tools, evaluating AI recommendations, and regulating their learning activities effectively. Similarly, Self-Regulated Learning Theory suggests that learners possessing higher cognitive and metacognitive competencies demonstrate stronger planning, monitoring, and reflection throughout the learning process (Zimmerman, 2000).

Recent empirical evidence supports the positive association between AI literacy and self-regulated learning. Students with greater AI literacy exhibit stronger goal-setting behaviors, improved learning management, enhanced metacognitive monitoring, and greater autonomy when completing academic tasks (Chan & Hu, 2023; Ifenthaler & Schumacher, 2023). These students are more capable of identifying credible AI-generated information, recognizing algorithmic limitations, and integrating AI into their learning without becoming overly dependent on technological assistance.

Moreover, AI literacy contributes to responsible AI use by encouraging students to verify information using multiple sources, recognize potential biases in AI-generated outputs, and make informed academic decisions. These competencies strengthen learners' metacognitive awareness and support independent learning behaviors that are central to self-regulated learning. In contrast, students with limited AI literacy may misuse AI technologies, rely excessively on automated responses, and

demonstrate weaker self-regulation because they lack the skills necessary to critically evaluate AI-generated content.

Despite growing recognition of AI literacy as a key twenty-first-century competency, empirical research examining its relationship with self-regulated learning remains limited. Most previous studies have investigated digital literacy rather than AI-specific literacy, while others have focused on technology adoption without examining how AI competencies contribute to autonomous learning behaviors. Furthermore, evidence from developing countries remains scarce despite the rapid adoption of generative AI in higher education. Addressing these gaps, the present study proposes that AI literacy positively influences students' self-regulated learning.

H5: AI Literacy has a significant positive effect on Self-Regulated Learning.

2.6 Critical Thinking and Self-Regulated Learning

Critical thinking has long been recognized as a fundamental competency for successful self-regulated learning (SRL). Self-regulated learners actively plan, monitor, evaluate, and adjust their learning strategies to achieve academic goals. These metacognitive processes require learners to critically assess information, reflect on their understanding, and make informed decisions regarding their learning activities. Consequently, students with stronger critical thinking skills are generally more capable of regulating their own learning effectively.

In AI-supported learning environments, critical thinking becomes even more essential because generative AI systems can produce information that is inaccurate, incomplete, or biased. Rather than accepting AI-generated responses uncritically, students must evaluate the credibility, accuracy, and relevance of AI outputs before incorporating them into their academic work. Critical thinking enables learners to compare AI-generated information with reliable sources, identify inconsistencies, recognize potential biases, and make independent academic judgments. These cognitive processes support effective monitoring and evaluation, which are core dimensions of self-regulated learning.

Recent educational research has consistently reported a positive relationship between critical thinking and self-regulated learning. Students who frequently engage in analytical reasoning, reflective judgment, and evidence-based evaluation demonstrate higher levels of goal setting, self-monitoring, strategic learning, and self-reflection. Similarly, studies investigating AI-supported education have shown that learners who critically evaluate AI-generated content are more likely to use AI as a cognitive support tool rather than as a substitute for independent thinking. This balanced use of AI promotes deeper learning, stronger metacognitive awareness, and improved academic performance.

From the perspective of Self-Regulated Learning Theory, critical thinking represents an essential cognitive process that supports the monitoring and control phases of learning. During these phases, learners continuously evaluate their progress, assess the effectiveness of learning strategies, and modify their approaches when necessary. Social Cognitive Theory further explains that learners possessing strong cognitive competencies are more likely to engage in self-monitoring and self-

reflective behaviors, resulting in higher levels of self-regulation. Therefore, critical thinking serves as an important psychological mechanism through which students effectively regulate their learning in AI-enhanced educational environments.

Despite increasing research on AI-assisted learning, relatively few studies have simultaneously examined the direct influence of critical thinking on self-regulated learning within higher education contexts, particularly in developing countries where AI integration is still emerging. Most previous studies have treated critical thinking as an independent learning outcome rather than as an important antecedent of self-regulated learning. Addressing this gap contributes to a better understanding of how higher-order cognitive skills enhance students' ability to manage their learning while interacting with AI technologies.

Accordingly, the following hypothesis is proposed:

H4: Critical Thinking has a significant positive effect on Self-Regulated Learning.

2.7 Mediating Roles of AI Literacy and Critical Thinking

Artificial intelligence technologies do not automatically improve students' learning outcomes. Instead, the educational benefits of AI largely depend on students' ability to understand AI systems and critically process the information they generate. Accordingly, AI literacy and critical thinking may function as important mediating mechanisms through which AI-assisted learning promotes self-regulated learning.

AI literacy enables students to understand the capabilities, limitations, ethical implications, and appropriate applications of AI technologies. Students with higher AI literacy are better equipped to evaluate AI-generated information, select suitable AI tools, and integrate AI responsibly into their learning activities. Consequently, AI-assisted learning may first enhance students' AI literacy, which subsequently strengthens their capacity to regulate their own learning through effective planning, monitoring, and evaluation.

Similarly, AI-assisted learning can stimulate students' critical thinking by encouraging them to question AI-generated responses, compare multiple information sources, evaluate evidence, and identify inaccuracies or biases. These analytical activities promote reflective thinking and metacognitive regulation, which ultimately improve self-regulated learning behaviors. Rather than accepting AI outputs passively, students who develop stronger critical thinking skills become active participants in constructing knowledge and managing their own learning processes.

Social Cognitive Theory explains these mediation mechanisms by suggesting that environmental factors influence learning outcomes through changes in learners' cognitive capabilities. AI-assisted learning provides technological resources and learning opportunities that improve AI literacy and critical thinking, which subsequently influence students' self-regulated learning behaviors. Likewise, Self-Regulated Learning Theory emphasizes that cognitive and metacognitive competencies are necessary mechanisms that translate learning experiences into effective self-regulation.

Previous studies have independently demonstrated that AI-assisted learning improves AI literacy and critical thinking, while both constructs positively influence self-regulated learning. However, limited empirical research has simultaneously examined their parallel mediating roles within a unified research model, particularly among university students in developing countries. Investigating these mediation mechanisms provides a more comprehensive understanding of how AI-assisted learning contributes to students' autonomous learning development.

Accordingly, the following hypotheses are proposed:

H6: AI Literacy mediates the relationship between AI-Assisted Learning and Self-Regulated Learning.

H7: Critical Thinking mediates the relationship between AI-Assisted Learning and Self-Regulated Learning.

2.8 Moderating Role of AI Self-Efficacy

AI self-efficacy refers to an individual's confidence in his or her ability to effectively use artificial intelligence technologies to accomplish learning tasks(Wang & Chuang, 2024). Students with high AI self-efficacy believe they can successfully learn new AI applications, solve problems encountered while using AI systems, and utilize AI tools to improve academic performance (Liang et al., 2023). This confidence influences not only technology adoption but also how effectively learners develop competencies associated with AI usage.

Social Cognitive Theory identifies self-efficacy as one of the strongest determinants of human behavior. Individuals with higher self-efficacy exhibit greater persistence, stronger motivation, and increased willingness to engage with challenging tasks. Within AI-supported learning environments, students who possess high AI self-efficacy are more likely to explore AI technologies, experiment with new learning applications, and actively seek opportunities to improve their AI competencies(Kim & Lee, 2024).

AI-assisted learning provides opportunities for students to interact with AI systems; however, the effectiveness of these interactions may depend on learners' confidence in using the technology. Students with stronger AI self-efficacy are expected to gain greater AI literacy from AI-assisted learning because they are more willing to explore advanced AI functions, evaluate AI-generated information, and learn through continuous experimentation(Anders & Dux Speltz, 2025; Qin et al., 2026). Conversely, students with lower AI self-efficacy may hesitate to engage deeply with AI technologies, thereby limiting the development of AI literacy(Yang et al., 2025).

Technology Acceptance Model also supports this moderating relationship by suggesting that users' beliefs regarding their ability to use technology influence technology utilization and learning outcomes. Students who are confident in their AI capabilities are more likely to perceive AI systems as useful and easier to use, thereby maximizing learning opportunities offered by AI-assisted education.

Although previous studies have demonstrated positive relationships between self-efficacy, technology acceptance, and digital competence, relatively few studies have examined AI self-efficacy as a moderating variable linking AI-assisted learning and AI literacy. This represents an important theoretical gap because learners may respond differently to AI-supported educational environments depending on their confidence in using AI technologies.

Therefore, the following hypothesis is proposed:

H8: AI Self-Efficacy positively moderates the relationship between AI-Assisted Learning and AI Literacy, such that the relationship is stronger among students with higher AI Self-Efficacy.

2.9 Theoretical Background

2.9.1 Social Cognitive Theory

Social Cognitive Theory (SCT), developed by Bandura (1986), provides a comprehensive framework for explaining how learning occurs through the reciprocal interaction of personal factors, behavioral processes, and environmental influences. According to SCT, individuals are active agents who regulate their own learning through observation, experience, reflection, and self-evaluation. One of the theory's central constructs is self-efficacy, which refers to individuals' beliefs regarding their capability to perform specific tasks successfully.

Within AI-supported education, AI-assisted learning represents the environmental influence, whereas AI literacy, critical thinking, self-efficacy, and self-regulated learning represent individual cognitive and behavioral responses. Students who possess greater confidence in using AI technologies are more likely to engage actively with AI systems, develop higher AI literacy, exercise stronger critical thinking, and regulate their learning more effectively. Accordingly, SCT provides the theoretical foundation for explaining the direct effects of AI-assisted learning, the mediating roles of AI literacy and critical thinking, and the moderating role of AI self-efficacy.

2.9.2 Self-Regulated Learning Theory

Self-Regulated Learning (SRL) Theory, proposed by Zimmerman (2000), explains how learners actively control and manage their own learning processes through planning, monitoring, regulating, and reflecting on their academic activities. Rather than being passive recipients of information, self-regulated learners establish learning goals, employ appropriate strategies, monitor their progress, and evaluate learning outcomes for continuous improvement.

The theory identifies three cyclical phases of self-regulation: forethought, performance, and self-reflection. AI-assisted learning technologies can support each phase by providing personalized learning resources, immediate feedback, adaptive recommendations, and opportunities for reflection. However, successful self-regulation depends on learners' cognitive capabilities, including AI literacy and critical thinking. Students who understand AI technologies and critically evaluate AI-generated information are

more capable of using AI strategically to improve their learning outcomes. Therefore, SRL Theory provides the primary theoretical explanation for the relationships among AI-assisted learning, AI literacy, critical thinking, and self-regulated learning.

2.9.3 Technology Acceptance Model

The Technology Acceptance Model (TAM), developed by Davis (1989), explains users' acceptance and utilization of information technologies through two fundamental beliefs: perceived usefulness and perceived ease of use. According to TAM, individuals are more likely to adopt technologies when they believe the technologies enhance their performance and are easy to operate.

In higher education, AI-assisted learning technologies are increasingly integrated into teaching and learning processes. Students who perceive AI tools as useful and manageable are more likely to use them frequently and effectively. Repeated interaction with AI systems enhances students' AI literacy and promotes critical engagement with AI-generated content. Furthermore, students possessing higher AI self-efficacy generally perceive AI technologies as easier to use, thereby strengthening the relationship between AI-assisted learning and AI literacy. Consequently, TAM provides a theoretical explanation for technology adoption behaviors within AI-supported educational environments.

2.9.4 Integration of Social Cognitive Theory, Self-Regulated Learning Theory, and Technology Acceptance Model

This study integrates Social Cognitive Theory, Self-Regulated Learning Theory, and the Technology Acceptance Model to provide a comprehensive explanation of how AI-assisted learning influences university students' self-regulated learning.

Social Cognitive Theory explains how AI-assisted learning environments shape learners' cognitive development through AI literacy, critical thinking, and AI self-efficacy. Self-Regulated Learning Theory explains how these cognitive capabilities translate into effective learning regulation through planning, monitoring, strategic learning, and self-reflection. Meanwhile, the Technology Acceptance Model explains why students engage with AI technologies by emphasizing perceptions of usefulness, ease of use, and technology acceptance.

The integration of these theories provides a multilevel explanation of the proposed research model. AI-assisted learning functions as the technological learning environment; AI literacy and critical thinking operate as cognitive mechanisms that mediate learning outcomes; AI self-efficacy strengthens learners' engagement with AI technologies; and self-regulated learning represents the ultimate educational outcome. This integrated theoretical framework addresses limitations of previous studies that relied on a single theoretical perspective and offers a more comprehensive understanding of how AI technologies promote autonomous learning among university students.

2.10 Research Model

Based on the integrated theoretical foundation presented in the preceding sections and the research gaps identified in the literature, this study proposes a conceptual model that examines how AI-Assisted Learning (AAL) influences Self-Regulated Learning (SRL) through the mediating roles of AI Literacy (AIL) and Critical Thinking (CT), while considering the moderating role of AI Self-Efficacy (AISE) (see Fig. 1 and Table 1). The proposed model integrates Social Cognitive Theory (SCT), Self-Regulated Learning Theory (SRLT), and the Technology Acceptance Model (TAM) to explain how technological, cognitive, and psychological factors collectively shape students' learning behaviors in AI-supported higher education environments.

Recent educational research has consistently demonstrated that AI-assisted learning enhances personalized learning experiences, promotes higher-order thinking, and improves students' independent learning capabilities. Nevertheless, existing studies have primarily examined the direct effects of AI-assisted learning on academic outcomes without adequately investigating the underlying cognitive mechanisms that explain these relationships. In particular, limited empirical evidence has simultaneously examined the mediating roles of AI literacy and critical thinking together with the moderating role of AI self-efficacy within a unified theoretical framework, especially in higher education institutions in developing countries.

Accordingly, this study employs mediation and moderation analyses to investigate both the direct and indirect mechanisms through which AI-assisted learning influences self-regulated learning. Rather than assuming a simple direct relationship, the proposed model explains how AI-assisted learning first develops students' AI literacy and critical thinking, which subsequently enhance their self-regulated learning behaviors. Furthermore, AI self-efficacy is proposed to strengthen the relationship between AI-assisted learning and AI literacy, suggesting that students with greater confidence in using AI technologies derive greater educational benefits from AI-assisted learning environments.

The proposed research model therefore provides a theoretically grounded and empirically testable framework for understanding how AI technologies contribute to students' autonomous learning in higher education. By integrating technological, cognitive, and motivational perspectives, the model offers a comprehensive explanation of the mechanisms through which AI-assisted learning promotes self-regulated learning.

Therefore, the conceptual model incorporates five primary constructs:

1. AI-Assisted Learning (Independent Variable)
2. AI Literacy (Mediator 1)
3. Critical Thinking (Mediator 2)
4. AI Self-Efficacy (Moderator)
5. Self-Regulated Learning (Dependent Variable)

The model captures both the direct effects of AI-assisted learning on self-regulated learning and the indirect effects operating through AI literacy and critical thinking, while simultaneously accounting for

the conditional influence of AI self-efficacy. Consequently, the proposed framework provides a comprehensive understanding of how AI-supported learning environments facilitate students' cognitive development and autonomous learning behaviors in higher education (see Fig. 1 and Table 1).

Table 1
Theoretical Mapping of Research Constructs

Identified Educational Factors	Proposed Model Variables	Theoretical Foundation
AI-supported personalized learning, intelligent tutoring systems, adaptive feedback, and generative AI	AI-Assisted Learning (Independent Variable)	Technology Acceptance Model (Davis, 1989); Social Cognitive Theory (Bandura, 1986)
Students' understanding of AI concepts, ethical AI use, AI evaluation skills, and responsible AI application	AI Literacy (Mediator 1)	Social Cognitive Theory (Bandura, 1986); Technology Acceptance Model (Davis, 1989)
Analytical reasoning, evaluation of AI-generated information, reflective judgment, and evidence-based decision making	Critical Thinking (Mediator 2)	Self-Regulated Learning Theory (Zimmerman, 2000); Social Cognitive Theory (Bandura, 1986)
Confidence in using AI technologies for academic tasks and solving AI-related learning problems	AI Self-Efficacy (Moderator)	Social Cognitive Theory (Bandura, 1986)
Goal setting, strategic learning, self-monitoring, self-evaluation, and reflective learning behaviors	Self-Regulated Learning (Dependent Variable)	Self-Regulated Learning Theory (Zimmerman, 2000)

3. Research Methodology

3.1 Research Design, Data Collection Method, Target Population, and Sampling Technique

This study adopted a quantitative, cross-sectional research design to examine the influence of AI-Assisted Learning on Self-Regulated Learning among university students while investigating the mediating roles of AI Literacy and Critical Thinking and the moderating role of AI Self-Efficacy. A cross-sectional design was considered appropriate because it enables the collection of data from respondents at a single point in time and facilitates the examination of relationships among multiple constructs within AI-supported learning environments.

Primary data were collected using a structured online questionnaire administered through KoboToolbox, with the survey link distributed via WhatsApp groups, university student associations, and social media

platforms. This online approach enabled efficient access to university students across different higher education institutions in Somalia who actively use AI technologies for academic purposes.

The target population comprised undergraduate, master's, and PhD students enrolled in public and private universities in Somalia. Participants were required to have prior experience using AI-powered learning technologies such as ChatGPT, Gemini, Microsoft Copilot, or similar AI applications to support their academic activities. The final sample consisted of 225 valid responses, of which 79.1% were male and 20.9% were female. Most respondents were between 24 and 29 years old (37.3%), followed by those aged 30–35 years (29.3%). Undergraduate students represented 63.6% of the sample, master's students 34.2%, and PhD students 2.2%. Additionally, 66.7% of participants were enrolled in private universities, while 33.3% attended public universities.

The study employed a non-probability convenience sampling technique, as participants were selected based on accessibility and their willingness to participate in the survey. This approach was appropriate because the study specifically targeted university students who had practical experience using AI-assisted learning tools, making probability sampling difficult within the available time and institutional constraints.

To determine the minimum required sample size, G*Power 3.1 was utilized following the recommendations of (Kang, 2021; Kaya et al., 2019). Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, statistical power of 0.95, and four predictors, the minimum required sample size was 129 respondents (see Fig. 2). The power analysis yielded an actual statistical power of 0.951, indicating adequate power for detecting significant relationships in multiple regression analysis. The final sample of 225 respondents substantially exceeded the minimum requirement, thereby providing sufficient statistical power for regression, mediation, and moderation analyses using Hayes' PROCESS Macro.

3.2 Instrumentation and Translation Procedure

The survey instrument was originally developed in English and adapted from previously validated measurement scales. Since the study was conducted among university students in Somalia, a translation and back-translation procedure (Brislin, 1986) employed to ensure linguistic accuracy and cultural appropriateness.

Initially, the questionnaire was translated from English into Somali by an experienced bilingual academic. Subsequently, an independent bilingual expert translated the Somali version back into English. The original and back-translated English versions were carefully compared to identify inconsistencies, and necessary revisions were made to ensure semantic and conceptual equivalence.

Prior to the main data collection, a pilot study involving 35 university students was conducted to assess the clarity, readability, and comprehensibility of the questionnaire items. Based on participants' feedback, minor wording modifications were introduced to improve clarity without altering the underlying meaning

of the measurement items. These procedures enhanced the content validity of the instrument and minimized potential measurement errors arising from language differences.

3.3 Questionnaire and Measurement Scale

Data were collected using a structured questionnaire comprising five latent constructs measured using established scales from prior studies. All measurement items employed a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

AI-Assisted Learning was measured using five items adapted from(Davis, 1989; Venkatesh et al., 2003). The items assessed students' perceptions regarding the usefulness and effectiveness of AI technologies in supporting academic learning. Example items include: (1) *AI-based learning tools help me understand course materials more effectively.* (3) *AI-assisted learning enhances my overall learning experience.* AI Literacy was assessed using five items adapted from (W. Ng, 2012; van Laar et al., 2017). These items measured students' ability to evaluate AI-generated information, use digital technologies responsibly, verify information from multiple sources, and solve academic problems using digital tools. Example items include: (1) *I can verify information generated by AI using multiple sources.* (2) *I understand how to use digital technologies responsibly.* AI Self-Efficacy was measured using five items adapted from (Bandura, 1982; Compeau & Higgins, 1995). The construct captures students' confidence in their ability to learn and effectively utilize AI technologies for academic purposes. Example items include: (1) *I am confident in my ability to use AI tools for learning.* (2) *I believe I can successfully use AI technologies to improve my learning outcomes.*

Self-Regulated Learning was measured using five items adapted from (Artino Jr, 2005; Zimmerman, 2000). The items evaluate students' goal setting, learning strategy use, self-monitoring, time management, and self-evaluation during the learning process. Example items include: (1) *I set specific learning goals before beginning academic tasks.* (2) *I evaluate my learning outcomes and make improvements.* Critical Thinking was measured using five items adapted from contemporary literature on AI-supported learning and critical thinking assessment. The items examine students' ability to critically evaluate AI-generated information before using it for academic purposes. Example items include: (1) *I critically evaluate AI-generated responses before using them.* (2) *Identify potential biases in AI-generated content.*

Overall, the questionnaire consisted of 25 measurement items, representing five latent constructs, demonstrated excellent reliability (α = .910), which exceeds the recommended threshold of .70 (Hair & Alamer, 2022; Taber, 2018). All constructs were operationalized using reflective measurement models and were subsequently evaluated for reliability and validity prior to hypothesis testing. The hypothesized relationships among the constructs were examined using Hayes (2023) PROCESS Macro through regression, mediation, and moderation analyses with 5,000 bootstrap resamples.

3.4 Common method bias (CMB)

To assess the potential issue of common method bias (CMB), Harman's single-factor test was conducted. All measurement items were entered into an unrotated exploratory factor analysis, and the total variance explained by the first unrotated factor was examined. The results indicated that the first factor accounted for 11.20% of the total variance, which is substantially below the recommended threshold of 50%(Podsakoff et al., 2003). Therefore, common method variance is unlikely to pose a significant threat to the validity of the study. These findings suggest that the observed relationships among AI-Assisted Learning, AI Literacy, Critical Thinking, AI Self-Efficacy, and Self-Regulated Learning are not attributable to measurement method bias, thereby supporting the robustness of the study's empirical result.

3.5 Regression Assumption Checks

Residual diagnostics for the self-regulated learning outcome model were examined to determine residual normality. The histogram of standardized residuals (Fig. 3) matched a normal distribution ($M = 2.35 \times 10^{-15}$, $SD = 0.991$, $N = 225$), whereas the normal P-P plot (Fig. 2) revealed observed cumulative probabilities tracking closely to the expected diagonal, with no major divergence in the mid-range. These diagnostics, taken together, provide support for the normality assumption of the regression-based path estimates.

4. Data Analysis and Results

4.1. Multicollinearity analysis

Before conducting the regression, mediation, and moderation analyses, multicollinearity was assessed to determine whether high correlations among the independent variables could adversely affect the stability of the regression coefficients. Multicollinearity was evaluated using Tolerance and Variance Inflation Factor (VIF) statistics. According to Hair et al. (2022), tolerance values greater than 0.20 and VIF values below 5.0 indicate that multicollinearity is not a serious concern. Likewise, Kock (2015) suggested a more conservative threshold of VIF < 3.3 to minimize collinearity problems and potential common method bias.

As presented in Table 2, the tolerance values ranged from 0.505 to 0.638, while the corresponding VIF values ranged from 1.566 to 1.979. All tolerance values exceeded the recommended minimum threshold, and all VIF values were substantially below both the conventional cutoff of 5.0 and the more conservative threshold of 3.3. These findings indicate that multicollinearity was not present among the predictor variables. Therefore, each construct contributed unique explanatory information to the regression models, supporting the stability, precision, and interpretability of the estimated regression coefficients.

Table 2
Collinearity Statistics

Model	Collinearity Statistics	
	Tolerance	VIF
AI-Assisted Learning	.551	1.816
Digital Literacy	.526	1.900
Self-efficacy	.505	1.979
Self-Regulated Learning	.638	1.566
VIF: variance inflation		

4.2 Pearson correlation analysis

Pearson correlation analysis revealed that all study variables were positively and significantly correlated with one another ($p < .01$). AI-assisted learning demonstrated moderate positive correlations with AI literacy ($r = .544$), AI self-efficacy ($r = .621$), critical thinking ($r = .450$), and self-regulated learning ($r = .490$). Critical thinking exhibited the strongest association with self-regulated learning ($r = .664$), suggesting that students with stronger critical thinking skills tend to demonstrate higher levels of self-regulated learning. Similarly, AI literacy showed a moderate positive relationship with self-regulated learning ($r = .538$), whereas AI self-efficacy was moderately associated with both AI literacy ($r = .585$) and self-regulated learning ($r = .444$). Collectively, these findings provide preliminary empirical support for the hypothesized relationships and justify proceeding to structural model analysis. The result presented in Table 3.

Table 3
Hypothesis Testing Results for Direct Relationships

Variable	**1**	**2**	**3**	**4**	**5**
1. AI-Assisted Learning	1				
2. AI Literacy	.544**	1			
3. AI Self-Efficacy	.621**	.585**	1		
4. Critical Thinking	.450**	.555**	.457**	1	
5. Self-Regulated Learning	.490**	.538**	.444**	.664**	1

4.3 Direct relationship analysis

The regression analysis was conducted to examine the direct relationships among the study variables. Table 1 presents the regression coefficients (β), standard errors (SE), *t*-values, and significance levels for the proposed hypotheses. H1 evaluates whether AI-Assisted Learning has a significant positive effect on Self-Regulated Learning. The results revealed that AI-Assisted Learning has a significant positive effect

on Self-Regulated Learning (β = 0.163, SE = 0.053, *t* = 3.062, *p* = 0.003). Therefore, H1 was supported. This finding indicates that greater engagement with AI-assisted learning is associated with higher levels of self-regulated learning among university students. H2 evaluates whether AI-Assisted Learning has a significant positive effect on AI Literacy. The regression results demonstrated a strong and statistically significant positive relationship between AI-Assisted Learning and AI Literacy (β = 0.482, SE = 0.050, *t* = 9.673, *p* < 0.001). Therefore, H2 was supported. This finding suggests that students who make greater use of AI-assisted learning tools tend to possess higher levels of AI literacy. H3 evaluates whether AI-Assisted Learning has a significant positive effect on Critical Thinking. The findings indicated that AI-Assisted Learning significantly and positively predicts Critical Thinking (β = 0.191, SE = 0.059, *t* = 3.238, *p* = 0.001). Consequently, H3 was supported. This result implies that the use of AI-assisted learning contributes to the development of students' critical thinking skills. H4 evaluates whether Critical Thinking has a significant positive effect on Self-Regulated Learning. The regression analysis revealed a strong positive and statistically significant relationship between Critical Thinking and Self-Regulated Learning (β = 0.497, SE = 0.059, *t* = 8.405, *p* < 0.001). Therefore, H4 was supported. Among all the direct relationships examined, Critical Thinking exerted the strongest positive influence on Self-Regulated Learning, emphasizing its pivotal role in enhancing students' ability to plan, monitor, and regulate their learning activities. **H5** evaluates whether AI Literacy has a significant positive effect on Self-Regulated Learning. The results showed that AI Literacy has a significant positive effect on Self-Regulated Learning (β = 0.176, SE = 0.064, *t* = 2.729, *p* = 0.007). Accordingly, H5 was supported. This finding indicates that students with higher levels of AI literacy are more likely to exhibit effective self-regulated learning behaviors.

Table 4
Hypotheses path relationship

Hypothesis	Path Relationship	β	SE	t-value	p-value	Decision
H1	AI-Assisted Learning → Self-Regulated Learning	0.163	0.053	3.062	.003	Supported
H2	AI-Assisted Learning → AI Literacy	0.482	0.050	9.673	< .001	Supported
H3	AI-Assisted Learning → Critical Thinking	0.191	0.059	3.238	.001	Supported
H4	Critical Thinking → Self-Regulated Learning	0.497	0.059	8.405	< .001	Supported
H5	AI Literacy → Self-Regulated Learning	0.176	0.064	2.729	.007	Supported

4.4 Mediation analysis

The mediation analysis was conducted using Hayes' (2022) PROCESS Macro with 5,000 bootstrap resamples to examine the mediating roles of AI Literacy and Critical Thinking in the relationship between

AI-Assisted Learning and Self-Regulated Learning. The significance of the indirect effects was determined using bias-corrected 95% bootstrap confidence intervals (CIs). An indirect effect was considered statistically significant when the confidence interval did not include zero. The results are presented in Table 6. H6 evaluates whether AI Literacy mediates the relationship between AI-Assisted Learning and Self-Regulated Learning. The results indicated a significant indirect effect of AI-Assisted Learning on Self-Regulated Learning through AI Literacy (indirect effect = 0.085, 95% Bootstrap CI = [0.007, 0.179]). Because the bias-corrected confidence interval excluded zero and the direct effect remained significant (β = 0.163, *p* = 0.003), H6 was supported. These findings indicate complementary partial mediation, suggesting that AI-Assisted Learning enhances Self-Regulated Learning both directly and indirectly by improving students' AI Literacy. H7 evaluates whether Critical Thinking mediates the relationship between AI-Assisted Learning and Self-Regulated Learning. The results revealed a significant indirect effect through Critical Thinking (indirect effect = 0.095, 95% Bootstrap CI = [0.014, 0.192]). Since the bias-corrected confidence interval did not include zero and the direct effect remained statistically significant (β = 0.163, *p* = 0.003), H7 was supported. The findings indicate complementary partial mediation, demonstrating that AI-Assisted Learning improves Self-Regulated Learning both directly and indirectly through the enhancement of students' Critical Thinking skills (see Table 5).

Table 5
Mediation Analysis Using Hayes (2022)

Hypothesis	Mediation Path	Direct Effect	Specific Indirect Effect	Bootstrap 95% CI	Decision	Mediation Type
H6	AI-Assisted Learning → AI Literacy → Self-Regulated Learning	0.163	0.085	[0.007, 0.179]	Supported	Partial Mediation (Complementary)
H7	AI-Assisted Learning → Critical Thinking → Self-Regulated Learning	0.163	0.095	[0.014, 0.192]	Supported	Partial Mediation (Complementary)

4.5 Moderation Analysis

The moderation analysis was conducted using Hayes' (2022) PROCESS Macro to examine whether AI Self-Efficacy moderates the relationship between AI-Assisted Learning and AI Literacy. The interaction effect was estimated using 5,000 bootstrap resamples, and statistical significance was determined based on the regression coefficient, *t*-value, *p*-value, and the bias-corrected 95% bootstrap confidence interval (CI). The results are presented in Table 7 and Fig. 3. **H8** evaluates whether AI Self-Efficacy positively moderates the relationship between AI-Assisted Learning and AI Literacy, such that the relationship is stronger for students with higher AI Self-Efficacy. The results revealed that the interaction

between AI-Assisted Learning and AI Self-Efficacy was positive and statistically significant (β = 0.164, SE = 0.052, *t* = 3.185, *p* = 0.002, 95% Bootstrap CI = [0.063, 0.265]). Since the confidence interval did not include zero, H8 was supported. The positive interaction coefficient indicates that AI Self-Efficacy strengthens the positive relationship between AI-Assisted Learning and AI Literacy. Specifically, students with higher levels of AI Self-Efficacy gain greater improvements in AI Literacy from AI-Assisted Learning than those with lower levels of AI Self-Efficacy. In other words, confidence in one's ability to effectively use AI technologies enhances the educational benefits derived from AI-assisted learning.

Overall, the moderation analysis demonstrates that AI Self-Efficacy serves as an important boundary condition in the relationship between AI-Assisted Learning and AI Literacy. The significant positive interaction suggests that the effectiveness of AI-assisted learning in developing AI literacy depends, in part, on students' confidence in using AI technologies. These findings underscore the importance of fostering AI Self-Efficacy alongside the implementation of AI-assisted learning environments, as students with stronger AI self-efficacy are more likely to maximize the learning benefits and develop higher levels of AI literacy (see Table 6 and Fig. 4).

Table 6
Moderation Analysis Using Hayes (2022)

Hypothesis	Relationship	β	SE	t-value	p-value	95% CI	Decision
H8	AI-Assisted Learning × AI Self-Efficacy → AI Literacy	0.164	0.052	3.185	.002	[0.063, 0.265]	Supported

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5. Discussion

This study examined the influence of AI-Assisted Learning on Self-Regulated Learning among university students and investigated the mediating roles of AI Literacy and Critical Thinking, as well as the moderating role of AI Self-Efficacy. Drawing on Social Cognitive Theory (Bandura, 1986), Self-Regulated Learning Theory (Zimmerman, 2000), and the Technology Acceptance Model (Davis, 1989), the findings provide empirical evidence that AI-assisted learning enhances students' self-regulated learning both directly and indirectly through the development of AI literacy and critical thinking. Furthermore, AI Self-Efficacy strengthens the relationship between AI-Assisted Learning and AI Literacy, highlighting the importance of students' confidence in effectively using AI technologies.

First, the results revealed that AI-Assisted Learning has a significant positive effect on Self-Regulated Learning. This finding supports the central premise of Self-Regulated Learning Theory, which suggests that digital learning technologies facilitate learners' ability to plan, monitor, and evaluate their own learning processes (Zimmerman, 2000; Panadero, 2017). AI-assisted learning environments provide personalized feedback, adaptive recommendations, and immediate learning support that encourage

students to become more autonomous learners. This result is consistent with previous studies demonstrating that AI-powered educational technologies enhance learner engagement, metacognitive regulation, and academic performance by promoting self-directed learning behaviors(Holmes et al., 2022;Zawacki-Richter et al., 2019)

Second, the findings indicate that AI-Assisted Learning significantly improves both AI Literacy and Critical Thinking. The strong positive relationship between AI-Assisted Learning and AI Literacy suggests that regular interaction with AI technologies enables students to develop a better understanding of AI concepts, capabilities, and ethical implications. This finding aligns with previous research emphasizing that practical exposure to AI applications enhances students' technological competence and digital literacy (Long & Magerko, 2020; Ng et al., 2021). Likewise, AI-Assisted Learning was found to positively influence Critical Thinking, indicating that AI-supported learning environments encourage students to analyze information, evaluate AI-generated content, compare alternative solutions, and make informed judgments. This supports recent educational research arguing that generative AI, when appropriately integrated into teaching and learning, can strengthen higher-order cognitive skills rather than merely automate learning tasks (Kasneci et al., 2023; Dwivedi et al., 2023).

Third, the study demonstrates that Critical Thinking and AI Literacy significantly predict Self-Regulated Learning, with Critical Thinking emerging as the strongest predictor. This finding suggests that students who possess stronger analytical and evaluative skills are better able to regulate their own learning activities. Critical thinkers are more capable of setting learning goals, evaluating information quality, reflecting on their learning progress, and making strategic learning decisions. Similarly, AI Literacy enables students to use AI tools effectively and responsibly, thereby supporting independent learning. These findings are consistent with Social Cognitive Theory, which emphasizes that cognitive competencies enhance learners' self-regulatory capabilities through improved self-monitoring and strategic behavior (Bandura, 1986). Previous studies have likewise reported that digital literacy and critical thinking are essential competencies for successful self-regulated learning in technology-enhanced educational environments (Zimmerman, 2008; Ng, 2012; van Laar et al., 2017).

Fourth, the mediation analysis revealed that both AI Literacy and Critical Thinking partially mediate the relationship between AI-Assisted Learning and Self-Regulated Learning. The use of Hayes' PROCESS Macro with 5,000 bootstrap resamples confirmed that both indirect effects were statistically significant, while the direct effect of AI-Assisted Learning remained significant, indicating complementary partial mediation. These findings suggest that AI-assisted learning enhances self-regulated learning not only through direct interaction with AI technologies but also by improving students' technological competence and higher-order cognitive skills. Notably, the indirect effect through Critical Thinking was slightly stronger than that through AI Literacy, implying that cognitive development constitutes the more influential mechanism linking AI-assisted learning to self-regulated learning. This finding extends previous studies by demonstrating the psychological processes through which AI-assisted learning contributes to autonomous learning and supports recent research emphasizing that AI technologies

improve educational outcomes by fostering learners' cognitive engagement and digital competencies rather than simply providing automated assistance (Holmes et al., 2022; Kasneci et al., 2023).

Fifth, the moderation analysis demonstrated that AI Self-Efficacy positively moderates the relationship between AI-Assisted Learning and AI Literacy. Specifically, the positive interaction effect indicates that students with higher AI Self-Efficacy benefit more from AI-assisted learning in developing AI literacy than students with lower levels of confidence in using AI technologies. This finding strongly supports Social Cognitive Theory, which identifies self-efficacy as a critical determinant of technology use, learning motivation, and performance (Bandura, 1997). Students who believe they are capable of using AI tools effectively are more willing to explore advanced AI applications, experiment with different learning strategies, and engage more deeply with AI-supported learning environments. Consequently, they acquire greater AI literacy through continued interaction with AI technologies. This finding is also consistent with previous technology adoption studies showing that self-efficacy enhances technology acceptance, digital competence, and learning outcomes across various educational contexts(Dahri et al., 2023; Peng et al., 2024; Zakir et al., 2025).

The findings provide several important practical implications for higher education institutions, educators, and policymakers. While AI-assisted learning directly improves students' self-regulated learning, universities should recognize that the greatest educational benefits are achieved when AI implementation is accompanied by initiatives that strengthen students' AI literacy, critical thinking, and AI self-efficacy. Rather than focusing solely on providing access to AI technologies, higher education institutions should integrate AI literacy into curricula, design learning activities that promote critical thinking, and offer training programs that build students' confidence in using AI responsibly and effectively. Such initiatives will enable students to maximize the educational potential of AI while developing the competencies required for lifelong learning in increasingly AI-driven educational and professional environments.

Collectively, these findings confirm the value of integrating Social Cognitive Theory, Self-Regulated Learning Theory, and the Technology Acceptance Model to explain how AI-assisted learning promotes students' self-regulated learning. The study extends the emerging literature on AI in higher education by demonstrating that AI-Assisted Learning influences Self-Regulated Learning through multiple pathways, including direct effects, complementary mediation through AI Literacy and Critical Thinking, and conditional effects determined by AI Self-Efficacy. By identifying these underlying mechanisms, the study contributes both theoretically and practically to understanding how universities can leverage AI technologies to cultivate autonomous, digitally competent, and critically engaged learners in the era of artificial intelligence.

Theoretical and Practical Implications

This study makes several important theoretical and practical contributions to the growing body of literature on AI-assisted learning and self-regulated learning, guided by the proposed conceptual

framework integrating Social Cognitive Theory (SCT), Self-Regulated Learning Theory (SRLT), and the Technology Acceptance Model (TAM).

First, the study advances the theoretical understanding of AI-assisted learning by integrating Social Cognitive Theory, Self-Regulated Learning Theory, and the Technology Acceptance Model into a single explanatory framework. While previous studies have primarily examined the direct educational benefits of AI technologies or students' acceptance of AI tools independently, this study demonstrates how AI-Assisted Learning influences Self-Regulated Learning through both cognitive and technological mechanisms. By incorporating AI Literacy and Critical Thinking as mediating variables and AI Self-Efficacy as a moderating variable, the study provides a more comprehensive explanation of how AI technologies contribute to autonomous learning. This integrated perspective extends existing AI-in-education research by explaining not only whether AI-assisted learning is effective but also the psychological and cognitive processes through which its educational benefits are realized.

Second, the study contributes to the literature by providing empirical evidence for the complementary mediating roles of AI Literacy and Critical Thinking. The mediation analysis demonstrates that AI-assisted learning enhances students' self-regulated learning not only directly but also indirectly by strengthening their AI literacy and critical thinking skills. Furthermore, the finding that Critical Thinking exerts a stronger indirect effect than AI Literacy highlights the importance of higher-order cognitive skills as a key mechanism through which AI technologies improve learning outcomes. These findings enrich the literature on AI-supported learning by identifying the underlying pathways that explain how AI-assisted learning translates into improved self-regulated learning, thereby extending previous research that has largely focused on direct relationships between AI use and academic performance.

Third, the study extends Social Cognitive Theory by validating the moderating role of AI Self-Efficacy in AI-assisted learning. The results reveal that AI Self-Efficacy strengthens the positive relationship between AI-Assisted Learning and AI Literacy, indicating that students' confidence in their ability to use AI technologies enhances the educational value derived from AI-supported learning environments. This finding contributes to theory by demonstrating that self-efficacy functions as an important boundary condition influencing the effectiveness of AI-assisted learning. Consequently, the study broadens the application of Social Cognitive Theory within AI-enabled educational contexts and provides empirical evidence that individual beliefs about technological capability significantly influence learning outcomes.

From a practical perspective, the findings offer several important implications for higher education institutions, educators, instructional designers, and policymakers. First, universities should move beyond simply providing access to AI technologies and instead develop comprehensive strategies that simultaneously promote AI literacy, critical thinking, and AI self-efficacy. AI-assisted learning environments should be designed not only to improve learning efficiency but also to cultivate students' ability to critically evaluate AI-generated information, make informed decisions, and regulate their own learning processes.

Second, the significant mediating roles of AI Literacy and Critical Thinking suggest that curriculum developers should integrate AI literacy education and critical thinking instruction across academic programs. Universities should incorporate practical AI applications, ethical AI use, information evaluation, prompt engineering, and AI-supported problem-solving activities into teaching and learning. Such initiatives will enable students to become competent and responsible users of AI technologies while strengthening the cognitive skills necessary for lifelong learning.

Third, the significant moderating effect of AI Self-Efficacy highlights the importance of building students' confidence in using AI technologies. Universities should provide workshops, hands-on training, mentoring programs, and guided practice opportunities that increase students' familiarity and confidence with AI tools. Enhancing AI self-efficacy will enable students to engage more effectively with AI-assisted learning environments and maximize the educational benefits of AI technologies.

Taken together, these theoretical and practical contributions advance both scholarly understanding and educational practice. The study integrates multiple theoretical perspectives, validates important mediating and moderating mechanisms, and provides evidence-based recommendations for the effective implementation of AI-assisted learning in higher education. By demonstrating how AI-Assisted Learning, AI Literacy, Critical Thinking, and AI Self-Efficacy jointly contribute to Self-Regulated Learning, the study offers a comprehensive framework for supporting students' academic success and preparing graduates with the digital competencies and autonomous learning skills required in the age of artificial intelligence.

Conclusion

This study examined the relationship between AI-Assisted Learning and Self-Regulated Learning among university students by investigating the mediating roles of AI Literacy and Critical Thinking and the moderating role of AI Self-Efficacy. Grounded in Social Cognitive Theory (SCT), Self-Regulated Learning Theory (SRLT), and the Technology Acceptance Model (TAM), the study provides empirical evidence that AI-assisted learning is an important driver of students' self-regulated learning in higher education.

The findings demonstrate that AI-Assisted Learning directly and positively influences Self-Regulated Learning, while also significantly enhancing students' AI Literacy and Critical Thinking. Both AI Literacy and Critical Thinking were found to positively predict Self-Regulated Learning, with Critical Thinking emerging as the strongest predictor. Furthermore, the mediation analysis revealed that both AI Literacy and Critical Thinking serve as complementary partial mediators, indicating that AI-assisted learning enhances students' self-regulated learning both directly and indirectly through the development of technological competence and higher-order cognitive skills. The moderation analysis further demonstrated that AI Self-Efficacy strengthens the positive relationship between AI-Assisted Learning and AI Literacy, suggesting that students with greater confidence in using AI technologies derive greater educational benefits from AI-assisted learning environments.

Overall, the findings highlight that the educational value of AI extends beyond improving learning efficiency. AI-assisted learning fosters the development of essential competencies including AI literacy, critical thinking, and self-efficacy—that enable students to become more autonomous, reflective, and effective learners. These results emphasize that successful AI integration in higher education requires not only the availability of AI technologies but also educational strategies that cultivate students' digital competencies, critical reasoning abilities, and confidence in using AI responsibly and effectively.

By identifying the direct, mediating, and moderating mechanisms linking AI-Assisted Learning to Self-Regulated Learning, this study contributes to the growing body of knowledge on AI in higher education and advances the theoretical understanding of AI-enabled learning. The findings also provide practical guidance for universities, educators, and policymakers seeking to design AI-supported learning environments that promote lifelong learning, digital competence, and student success. As artificial intelligence continues to reshape educational practice, fostering AI literacy, critical thinking, and AI self-efficacy will be essential for preparing university students to thrive in increasingly technology-driven learning and professional environments.

Limitations and future research direction

Despite the valuable contributions of this study, several limitations should be acknowledged.

First, the study employed a cross-sectional research design, with data collected from university students at a single point in time. Although the regression, mediation, and moderation analyses provide evidence of significant relationships among the study variables, the cross-sectional nature of the data limits the ability to establish causal relationships or temporal ordering between AI-Assisted Learning, AI Literacy, Critical Thinking, AI Self-Efficacy, and Self-Regulated Learning. Future studies should adopt longitudinal research designs to examine how students' AI usage and learning competencies evolve and to better establish causal pathways.

Second, this study relied exclusively on a quantitative survey approach, which limited the ability to capture students' personal experiences, perceptions, and learning behaviors associated with AI-assisted learning. While the quantitative findings provide robust statistical evidence, they do not fully explain the underlying reasons why AI-assisted learning influences AI literacy, critical thinking, or self-regulated learning. Future research should employ mixed-methods or qualitative approaches, such as interviews, focus groups, classroom observations, or learning diaries, to provide richer insights into students' experiences with AI technologies and the cognitive processes underlying AI-supported learning.

Third, all variables were measured using self-reported questionnaires, which may introduce common method variance, response bias, and social desirability bias. Students may have overestimated their AI literacy, critical thinking, self-efficacy, or self-regulated learning behaviors. Future studies should incorporate multiple data sources, including instructor assessments, objective learning analytics, AI system usage logs, academic performance records, or behavioral tracking data, to improve the validity and reliability of the findings.

Fourth, the study focused exclusively on university students, which may limit the generalizability of the findings to other educational settings. Students in secondary schools, vocational education, or lifelong learning environments may exhibit different patterns of AI usage and self-regulated learning. Future research should validate the proposed model across diverse educational contexts, disciplines, and age groups to determine the robustness and generalizability of the findings.

Furthermore, although the study identified AI Literacy and Critical Thinking as important mediating mechanisms and AI Self-Efficacy as a significant moderator, other relevant psychological and educational factors may also influence the relationship between AI-Assisted Learning and Self-Regulated Learning. Future research could investigate additional mediators such as metacognitive awareness, learning motivation, cognitive engagement, digital resilience, trust in AI, academic self-efficacy, and learning strategies. Likewise, additional moderators including instructor support, AI anxiety, institutional AI readiness, technology accessibility, learning styles, and prior AI experience could provide a more comprehensive understanding of the conditions under which AI-assisted learning is most effective.

Finally, future studies should examine the impact of different AI applications rather than treating AI-assisted learning as a single construct. Comparative investigations of generative AI tools (e.g., ChatGPT), intelligent tutoring systems, adaptive learning platforms, learning analytics, and AI-powered assessment systems could reveal whether different AI technologies contribute differently to AI literacy, critical thinking, and self-regulated learning. Cross-cultural and cross-country comparative studies would also provide valuable insights into how educational systems, cultural contexts, and digital infrastructure influence the effectiveness of AI-assisted learning.

Overall, addressing these limitations would strengthen the theoretical and empirical understanding of AI-assisted learning in higher education. Future research adopting longitudinal, mixed-methods, multi-source, and cross-cultural approaches will provide deeper insights into the mechanisms through which artificial intelligence supports students' cognitive development, digital competence, and self-regulated learning, thereby informing more effective AI integration in higher education.

Declarations

Declarations Section

Ethics Approval and Consent to Participate

Ethical approval for this study was obtained from the Research Ethics Committee of Salam University, Somalia. The research protocol was reviewed and approved in accordance with the *Declaration of Helsinki* and the institutional research ethics guidelines of Salam University. All participants were informed about the study’s purpose and procedures, and voluntary participation was ensured. Written informed consent was obtained from all participants prior to data collection.

Human ethics and Consent to Participate Declarations

All procedures performed in this study involving human participants were conducted in accordance with ethical standards. Informed consent was obtained from all individual participants.

Clinical Trial Registration

Clinical trial number: not applicable.

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Conflict of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Authors' Contributions

Ali Abdi Mohamed: Conceptualization, Methodology, Data Collection, Writing – Original Draft. **Mohamud Hassan Abdulle:** Data Analysis, Validation, Writing – Review & Editing. **Abdulkadir Jeilani Mohamud:** Data Visualization, Technical Support, Final Manuscript Approval.

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Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Figures

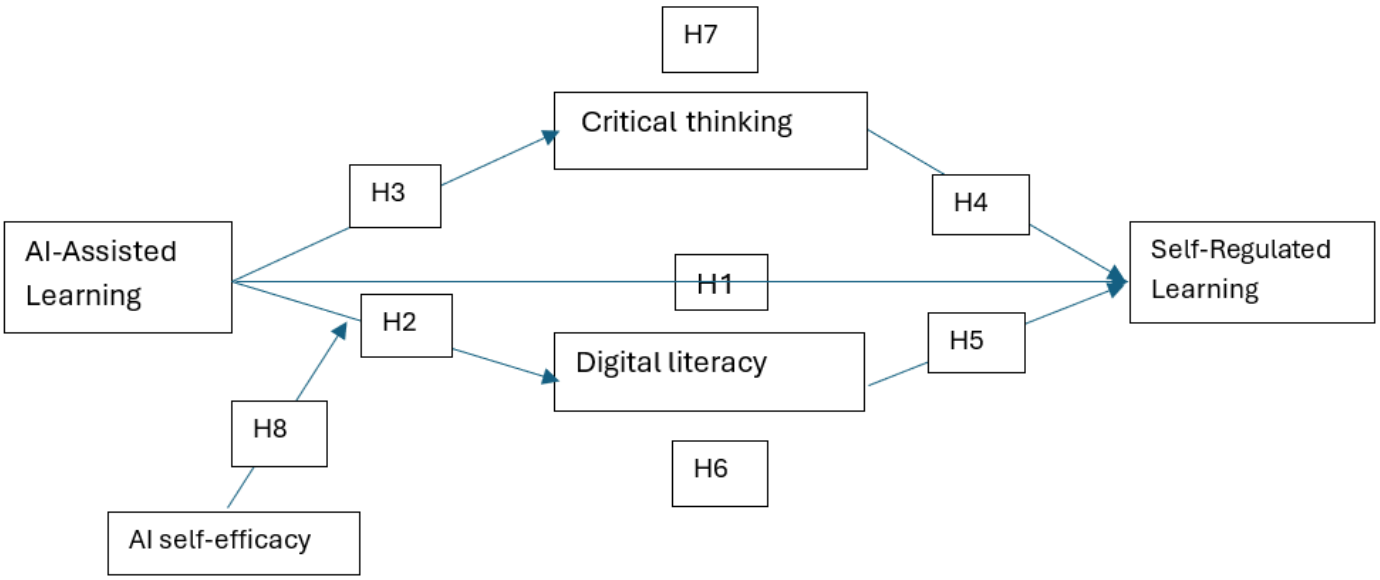


Figure 1

Research model

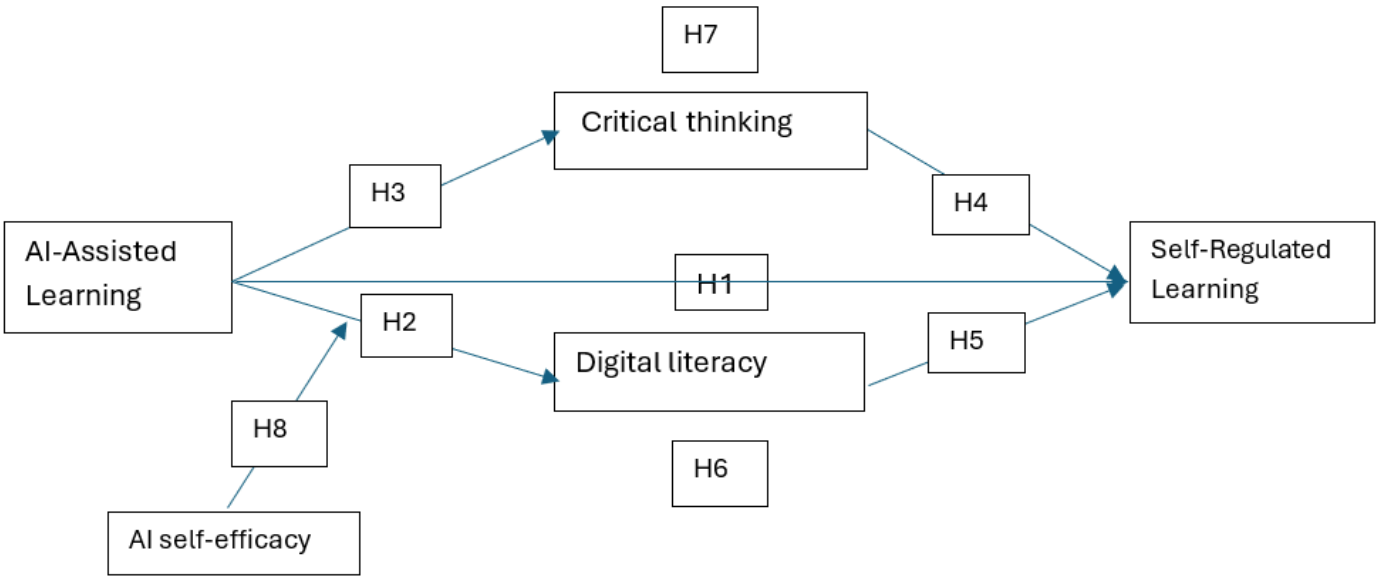


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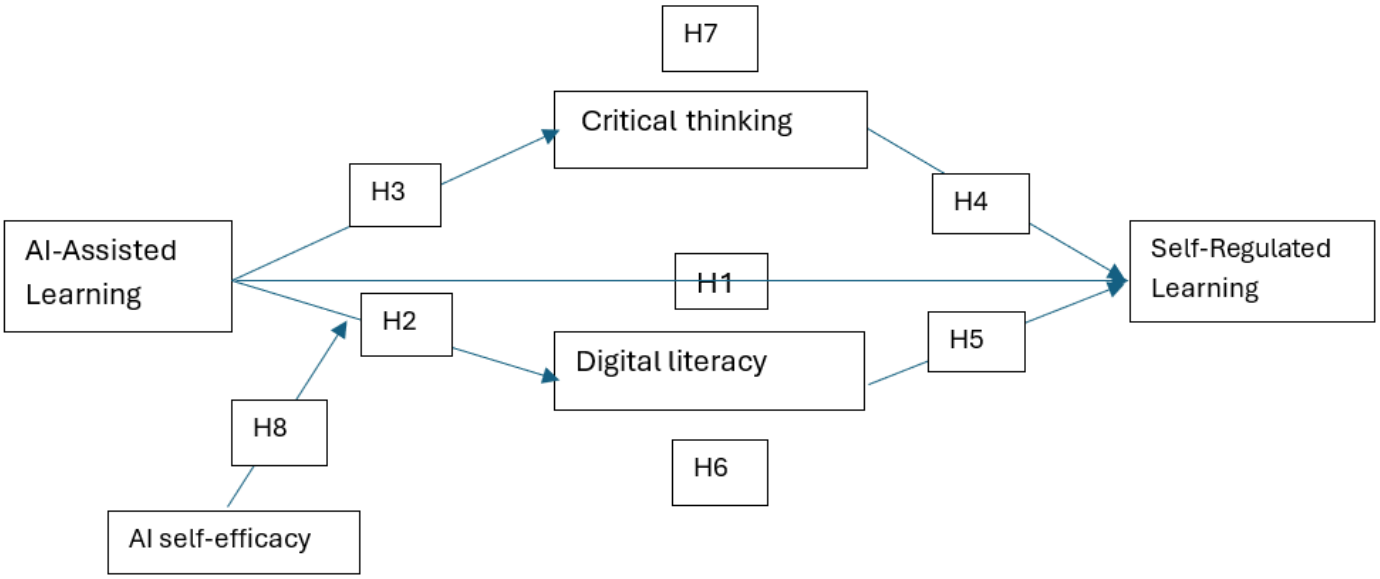


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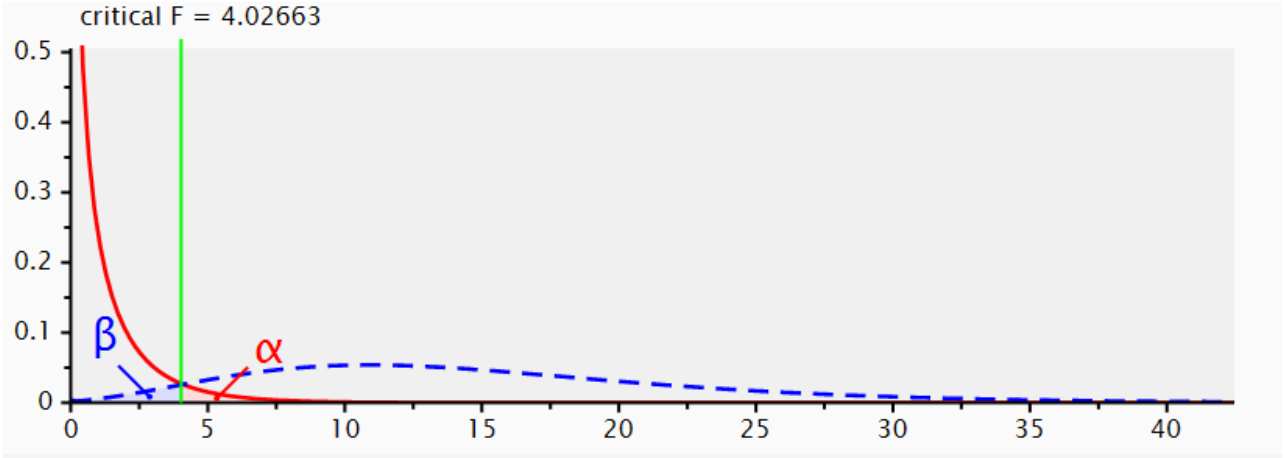


Figure 2

G power analysis

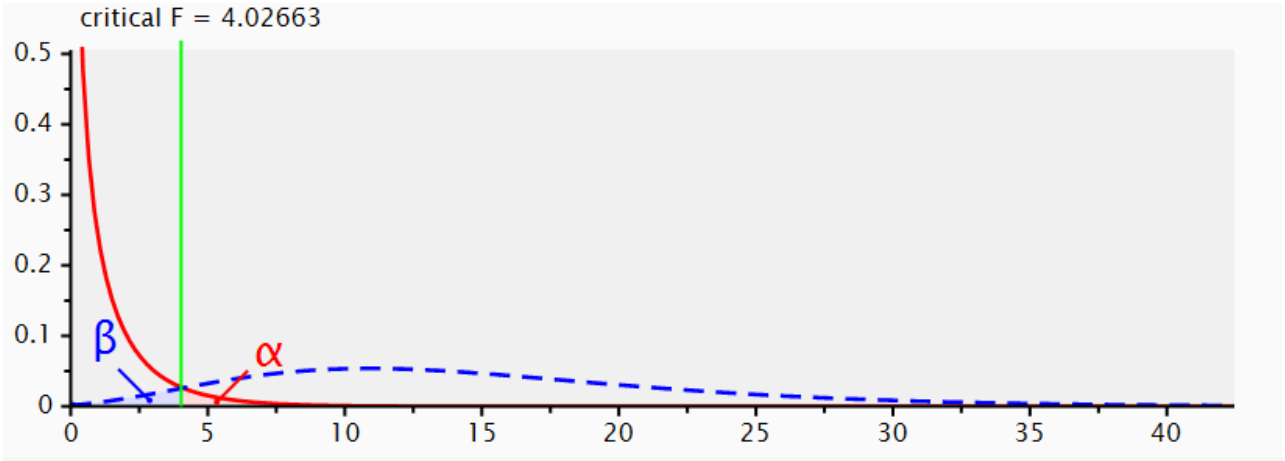


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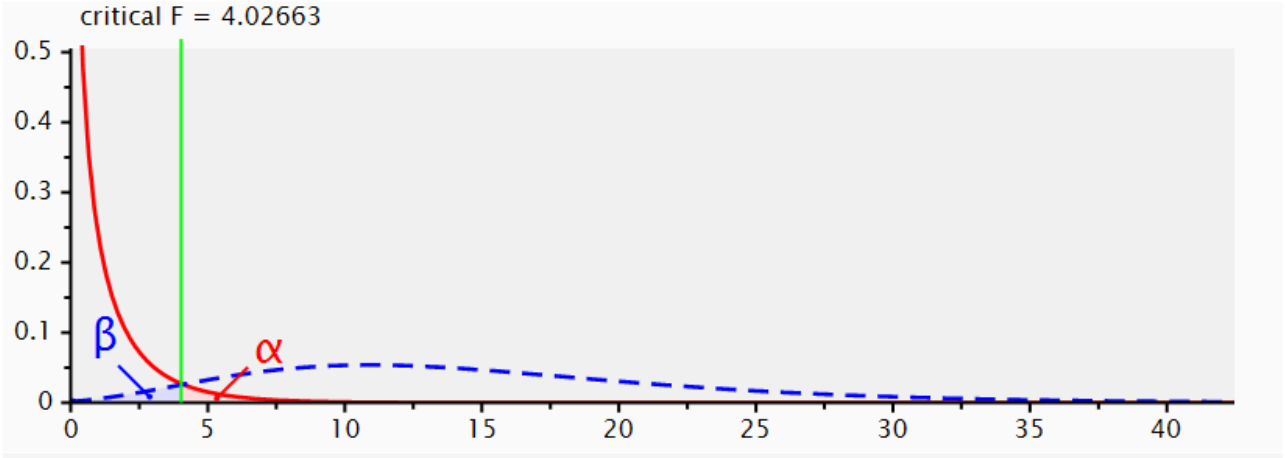


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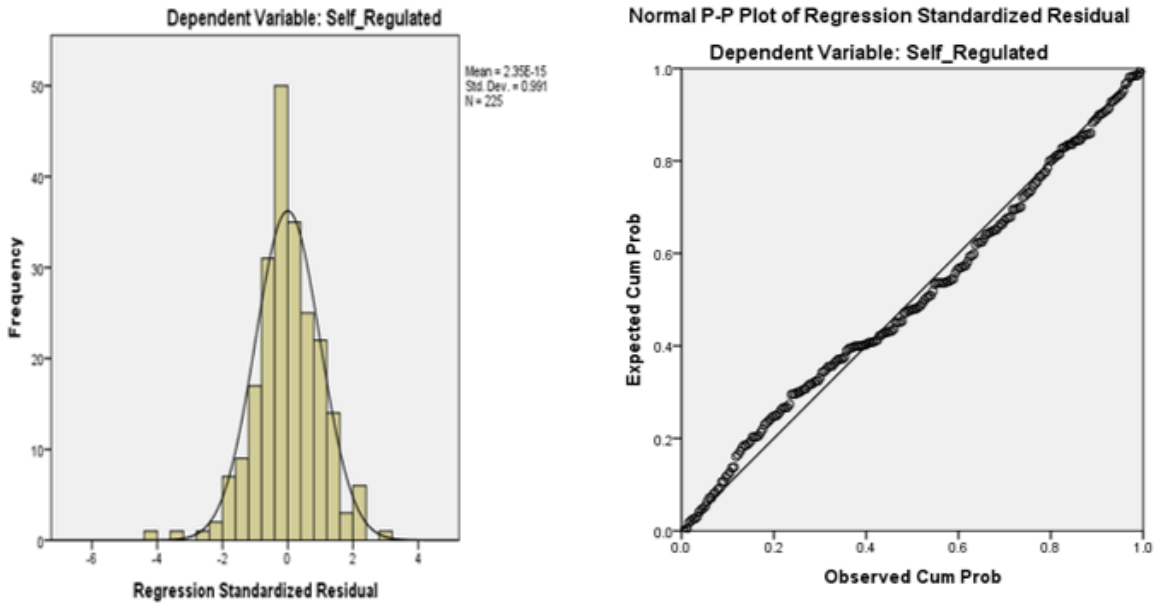
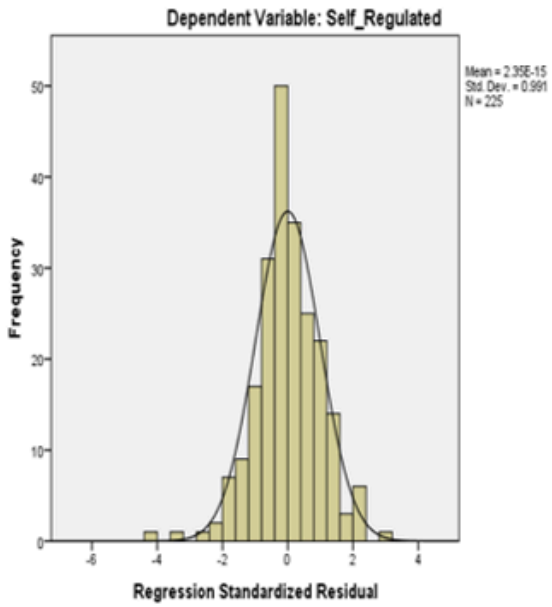


Figure 3

Assumption Checks



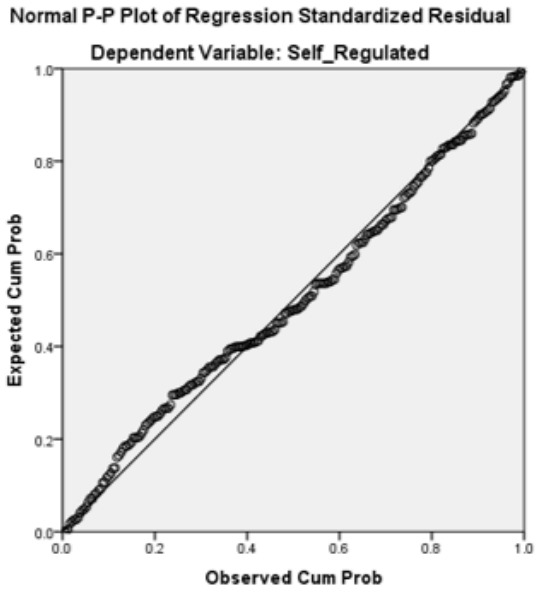
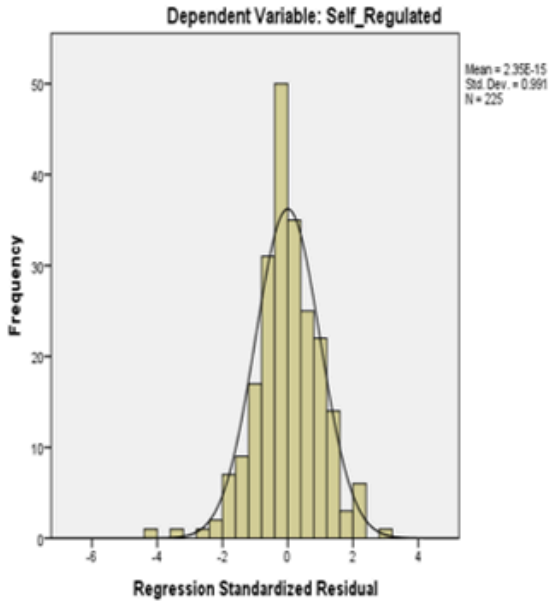


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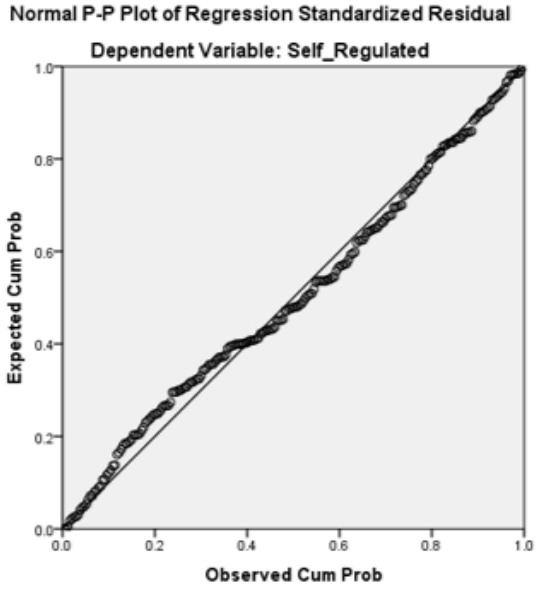


Figure 3

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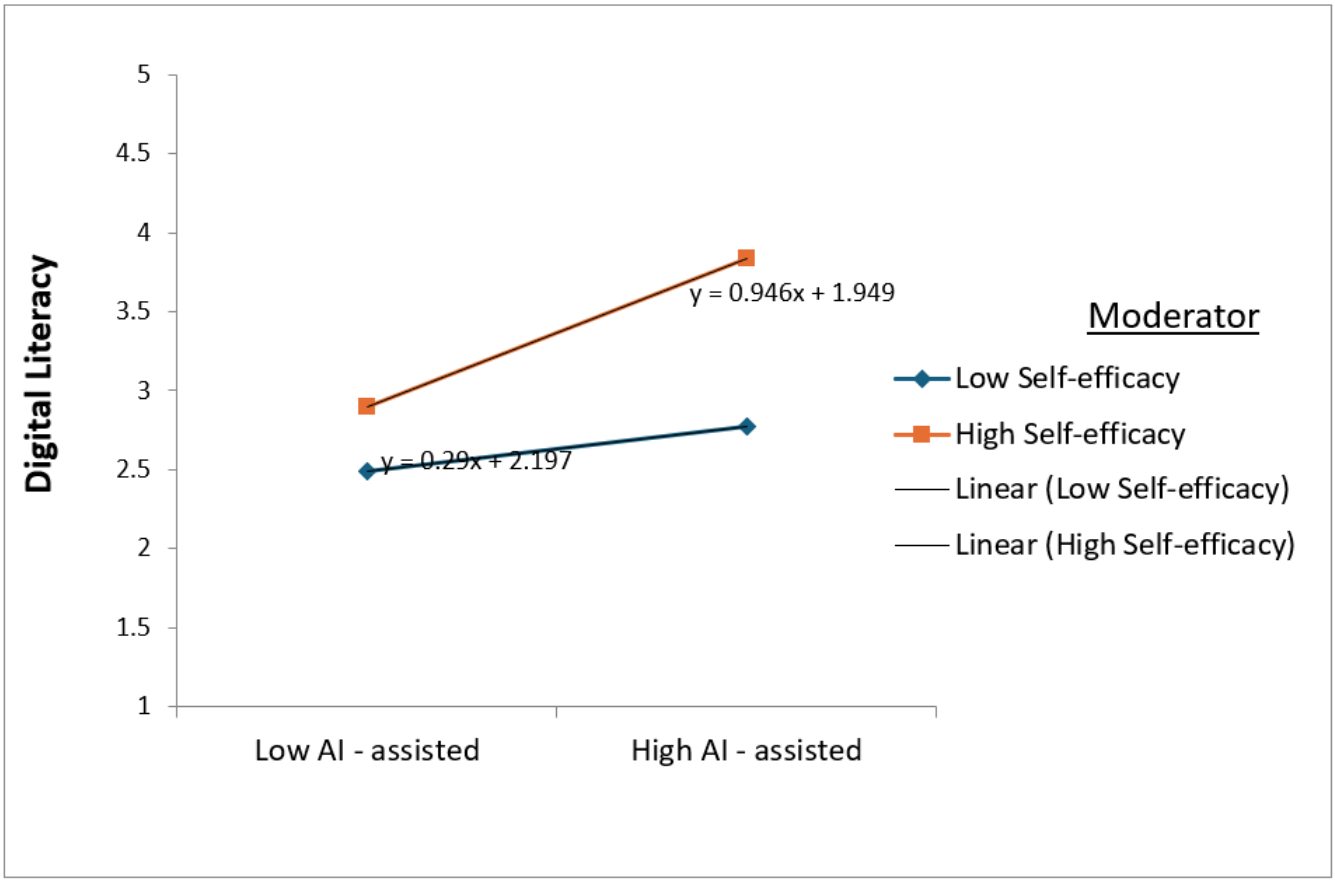


Figure 4

Moderating analysis

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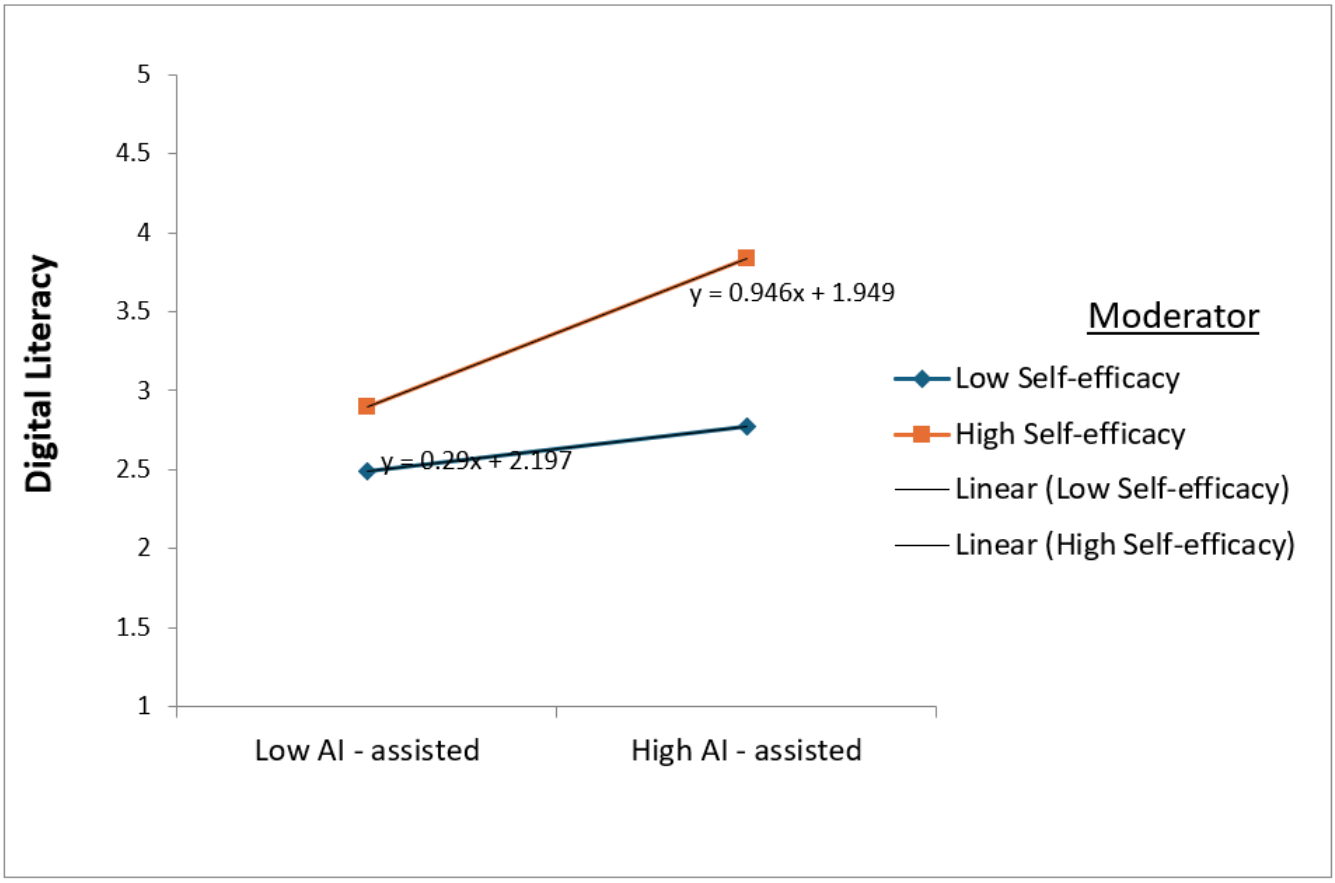


Figure 4

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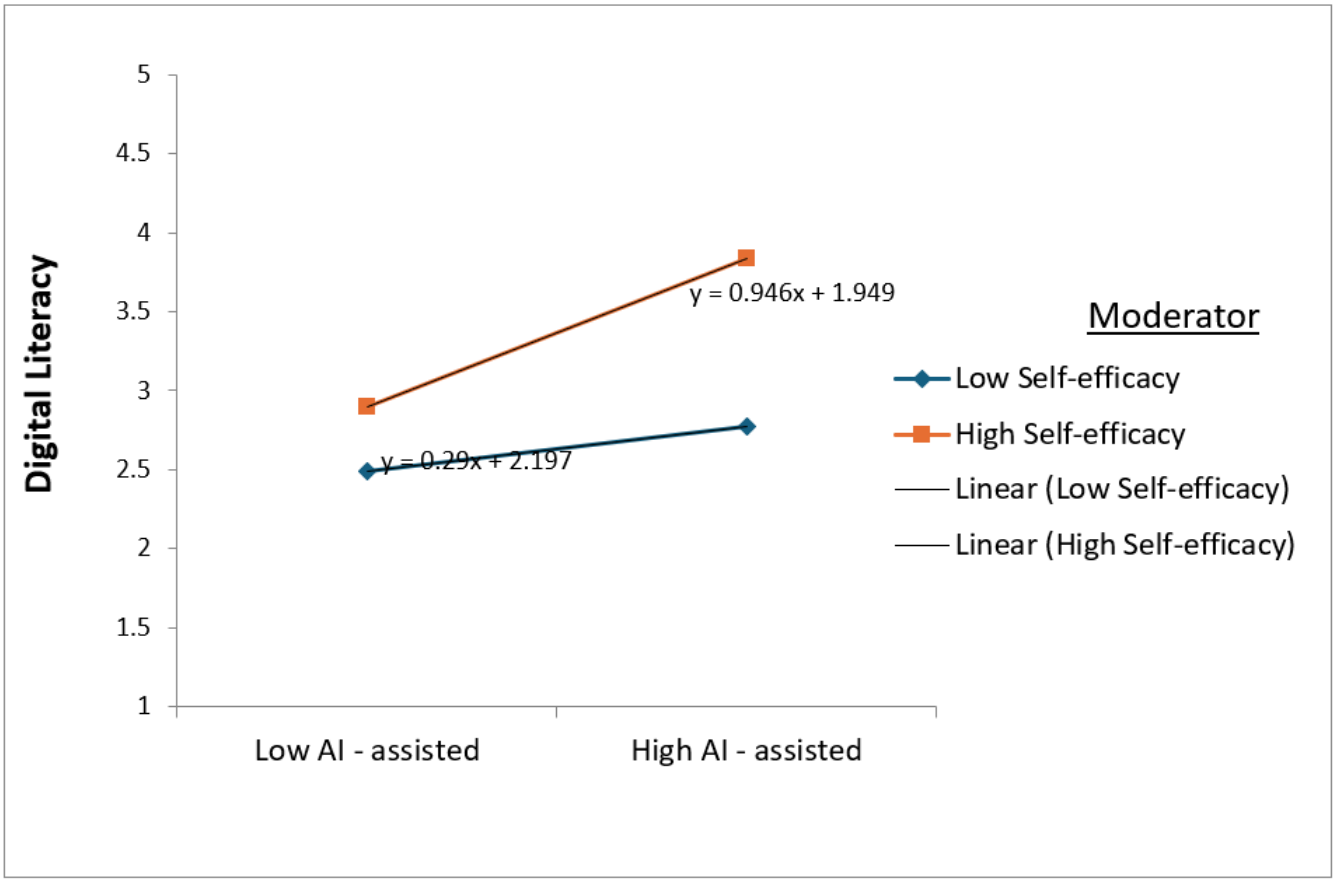


Figure 4

Moderating analysis